Improved Team Game Optimization Algorithm Based Solar MPPT with Fast Convergence Speed and Fast Response to Load Variations

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Abstract- Maximum power point tracking is one of the crucial components to ensure the PV system operates optimally. The bypass diodes are added across series-connected PV modules to avoid the hotspot phenomenon which resulted in the multiple peaks on the power-voltage curve during partial shading conditions. In this paper, a new metaheuristic approach, namely Improved Team Game optimization algorithm, has been proposed. Only one tuning parameter is required for the proposed algorithm and a new approach has been introduced to increase the convergence speed. Apart from that, a constant current method has been proposed during load variation conditions which improved the response of the system towards load changes by 78.26%. The experimental results showed that the convergence speed of the proposed method is 72.5% faster than the standard team game optimization algorithm. The proposed method also validated under different shading conditions and proved to have an average MPPT efficiency of 99.78% and an average tracking time of 0.9 s. The comparison between the proposed method and different metaheuristic approaches was also carried out based on grade point average and it showed the effectiveness of the proposed algorithm with a higher number of features.

Index Terms— Maximum Power Point Tracking, Partial shading condition, Global Maximum Power Point, Team Game Optimization Algorithm, and metaheuristic algorithm.

I. INTRODUCTION

Photovoltaic (PV) systems received tremendous attention with considerable investments in the last decade [1]. Greenhouse effect, depletion of primary energy sources (such as coal, fossil fuel, etc.), increase energy demand, abundant availability and renewability are common reasons for the increasing popularity of PV [2]. Extensive improvements are proposed in the literature to increase the efficiency of the PV system due to its non-linear nature. One of the hot topics of research is maximum power point tracking (MPPT) to ensure that the system working optimally. As shown in Fig. 1, the power-voltage (P-V) and current-voltage (I-V) curve of PV are non-linear in nature. The current is maximum (I_{max}) at short circuit current (I_{sc}), whereas the voltage is maximum at open-circuit voltage (V_{oc}). The tracking of maximum power point (MPP), the product of voltage at MPP (V_{mpp}) and current at MPP (I_{mpp}), is able to cause an increase in efficiency by 30% as compared to system without MPPT [3]. Initially, Fox et al. in 1979 [4] proposed the MPPT to the scientific world and it is followed by a high number of research articles on MPPT which focus on the improvement of tracking time and MPPT efficiency [5].

The conventional MPPT algorithms such as perturb and observe (P&O) [6], incremental conductance (InC) [7] and constant current (CC) [8] methods have fast tracking speed. However, bypass diodes are connected across the modules in order to avoid the hotspot phenomenon during the partial shading condition (PSC), and this causes the appearance of multiple peaks on the P-V curve as shown in Fig. 1 [9]. The multiple peaks consist of one global maximum power point (GMPP) and multiple local maximum power points (LMPPs) [10]. During PSC, conventional MPPT algorithms cannot always track the GMPP under all partial shading patterns and may converge to LMPP (point C or D). This causes less power transfer to the load and power losses as illustrated in Fig. 1. Furthermore, there is an issue of oscillation around MPP in the conventional MPPT controllers and parameter tuning of PID/PI

![Fig. 1. P-V and I-V Curve under uniform shading and PSC.](image-url)
is required due to the indirect control of duty cycle to decide the step size for duty cycle update. Then, the update direction of duty cycle is depended on the type of converter (i.e., from buck to boost).

With the advent of high-speed digital microcontrollers, the disadvantages of conventional MPPT algorithms are overcome by artificial intelligent (AI) based MPPT algorithms such as the artificial neural network (ANN) [11], fuzzy logic controller (FLC) [12] and adaptive network-based fuzzy interference system (ANFIS) [13]. The ANN and FLC perform better under PSCs as compared to traditional MPPT algorithms but training the vast amount of data with prior PV system knowledge, controlled variables, fixed membership functions and the need for significant memory complicate them. Furthermore, according to [14], they may trap at LMPP and struggle to follow GMPP accurately when complex PSC variability occurs.

The state of the art MPPT algorithms are bio-inspired or metaheuristic algorithms. These are usually population-based approaches in which multiple search particles (duty cycle, D) are initialized in a search space at different positions to determine the PV power at each position. The information of power is shared between the searching particles. Based on the information, each particle updates its position in the next iteration and converges towards the best duty cycle (D_{best}^1(t)), which is corresponding to the best particle power (P_{best}^1(t)) as shown in Fig. 2. These algorithms are simpler as compared to conventional and AI-based algorithms because no data training and prior knowledge about PV parameters required, direct control of duty cycle is possible, no modification required to the duty cycle step size update direction with the change in the converter, no oscillation around GMPP once the peak point is tracked and no requirement of high storage facility makes its implementation simple, robust and cost-effective. However, there are still a few complexities in the metaheuristic algorithms. Firstly, the metaheuristic algorithms require tuning parameters which varies with different PV array size and system design. In particle swarm optimization (PSO) [15], three tuning parameters (C_1, C_2 and w) are utilized, whereas in grey wolf optimization (GWO) [16], one tuning parameter (a) is required. These tuning parameters are not formulated and given a constant value based on the trial and error method.

Secondly, the tracking time of bio-inspired algorithms is higher in comparison with conventional MPPT algorithms [17]. One of the reasons is that the swarm-based bio-inspired algorithms such as artificial bee colony (ABC) [18], flower pollination [19], firefly [20] and bat [21] have a tendency to explore the position which was explored in the previous iteration repeatedly. As shown in Fig. 2, four particles are utilized to determine the peak point, and the initial position of four particles is at D_1^1(1), D_2^1(1), D_3^1(1) and D_4^1(1) respectively. While the four particles step towards the best position D_{best}^1(t) corresponding to best power P_{best}^1(t) through their respective position update equation, there is a high possibility that the particles could explore the positions again which are explored in the previous iterations. Thus, the termination condition would take a longer time to satisfy and stabilize the D. This problem is shown in the example given in Fig. 2 where D_4^3(1) is equal to D_3^1(1) and D_3^1(1) is equal to D_2^3(1).

Thirdly, the re-initialization of particles has been introduced in the bio-inspired algorithms if the input power (P_{PV}) varies after the GMPP (P_{mpp}) is tracked, such as in ARMO [22], bat and ant colony [23]. After the GMPP is tracked, the P_{PV} variation can occur due to the variation in solar intensity or load. The GMPP does not change when load variation occurs and only the D value for GMPP changes. Hence re-initialization of particles will cause a slower response during load variations. In order to increase the system’s response to load changes, the re-initialization of the particles has been avoided and with the aid of the impedance conversion equation of the respective dc-dc converter, the GMPP is tracked back during load variations in improved differential evolution (IDE) [24]. However, the issue is the high dependency on topology utilized. If the dc-dc converter is changed (suppose from boost to buck-boost), the modification in the algorithm is required.

In order to address these issues, an improved team game optimization algorithm for MPPT (ITGA-MPPT) has been proposed in this paper. This proposed controller can track the GMPP under rapidly varying shading conditions with one tuning parameter. The proposed controller is also able to avoid the repetitive exploration of the same position which explored before by another particle in the search space, thus a high convergence speed (CS) is achieved. A constant current (CC) method has been hybridized with ITGA in order to avoid the re-initialization of the position during load variations which improve the response to load changes significantly and it can be applied to any conventional isolated or non-isolated dc-dc converter without altering the direction to duty cycle update.

In order to elaborate on the above contributions, the standard Team Game Algorithm (TGA) has been introduced with its operating principle in section II. In section III, PV system behavior during shading and load variations has been elaborated. Section IV discussed the improvization to the standard TGA based on the observations through section III. Section V dedicated to results and discussion to verify the feasibility of the proposed method. In order to validate the efficacy of the proposed method, it was compared with other popular metaheuristic algorithms used for MPPT through the cumulative grade point average (CGPA) in Section VI. Section VII concludes the paper with a future recommendation.
II. TEAM GAME OPTIMIZATION ALGORITHM

The team game optimization algorithm (TGA) is a population-based metaheuristic approach proposed by Mahmoodabadi in 2018 [25]. The significant advantage of the proposed algorithm is that no tuning parameter is required based on the trial and error method and thus reduce the complexity of the algorithm. It is inspired by a team game where players are divided into two teams, particles are players and their performances are measured by their stamina. Passing a ball, making mistakes and substitution are the three operations each player is eligible to perform.

A. Initialization

The process starts with the initialization of $n$ player’s position randomly. The $n$ number of players are divided into two teams equally, where $x_{iA}$ represents the player in team A and $x_{iB}$ for the player in team B as in (1) and (2).

$$A = [x_{iA}, x_{2A}, x_{3A} ...]$$

$$B = [x_{1B}, x_{2B}, x_{3B} ...]$$

B. Passing operation

The passing of a ball is shown through Fig. 3(a) and (b). $C_i$ in (3) is a communication factor between a player having a ball $x_i(t)$, the captain of the team $x_{best}(t)$, who is regarded as the best player, and a random player $x_{rand}(t)$. Whereas $r$ in (4) stands for the random number between 0 and 1 generated from Gaussian plane distribution.

$$C_i(t + 1) = 2. x_{best}(t) - x_i(t) - x_{rand}(t)$$

$$x_i(t + 1) = x_i(t) + r \times C_i(t + 1)$$

C. Mistake operation

The mistake operator is performed when the probability condition is satisfied. In this operation, the player who owns the ball contacts with the player from the opponent team. This condition is satisfied. In this operation, the player who owns the ball is unable to improve his profile, a fresh player with a random position will be substituted. Furthermore, a constant complexity of the algorithm. It is inspired by a team game and their performances are measured by their stamina. Passing a ball, making mistakes and substitution are the three operations each player is eligible to perform.

D. Substitution property

The player’s profile will be checked after each iteration. If the player is unable to improve his profile, a fresh player with a random position will be substituted. Furthermore, a constant complexity of the algorithm. It is inspired by a team game and their performances are measured by their stamina. Passing a ball, making mistakes and substitution are the three operations each player is eligible to perform.

E. Out of the field players

Once the profile of the players updated, then the position of each player will be checked to ensure they are in the limit of the search space. Otherwise, the out of the search space player position will get reset with a new random position. The process will continue until the termination condition is achieved.

III. PV SYSTEM BEHAVIOR UNDER PARTIALLY SHADED, SOLAR INTENSITY AND LOAD VARIATION CONDITIONS

Fig. 4 shows the uniformly and partially shaded I-V curves for a PV system using 175 W PV array. If four duty cycles $D_1(1)$, $D_2(1)$, $D_3(1)$ and $D_4(1)$ (0.2, 0.4, 0.6 and 0.8) are used as the initial positions for the proposed algorithm, the power for each positions are as shown in Fig. 4. Then, the particles will evolve through each iteration and converge to the GMPP. As shown in Fig. 4, GMPP for different I-V curves are located between the two positions which have the higher power among all positions (we call these two positions the two best points in this paper). This phenomenon also found true in the complex shading conditions where the GMPP located at the extreme left or right of the I-V curve. Therefore, this paper proposed that the two best duty cycles update their position by normal updating equation of the respective metaheuristic method while the remaining two duty cycles update their position only in the area between the two best duty cycles. Thus, this technique will reduce the search space for GMPP and improve the CS. At the same time, it also helps to reduce the oscillation of power during the tracking process.

Fig. 4. Power response with fixed duty cycle initial position.

Then, the different I-V curves during solar intensity variation are shown in Fig. 5. When the MPP for PSC-B is tracked with $V_{mpp}, 25.53$ V and $I_{mpp}, 2.329$ A and the shading condition has shifted to PSC-C after some time, the operating point changed from point B to C. Both of the $V_{PV}$ and $I_{PV}$ are decrease (16.99 V and 1.54 A) as compared to the tracked $V_{mpp}$ and $I_{mpp}$ under PSC-B. Meanwhile, the operating point changes from point B to A if the shading condition changes from PSC-C to PSC-B. Both of the $V_{PV}$ and $I_{PV}$ increase (39.35 V and 3.568 A) as compared to the tracked $V_{mpp}$ and $I_{mpp}$ under PSC-B. This observation shows that both the current and voltage vary in the same direction during the solar intensity variation as shown in (6).

$$\begin{align*}
0.578 - 0.0046 \text{ (c) 2020 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.}
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Initialization of the metaheuristic approaches. This can be done by fixed perturbation of duty cycle with delta D (dD) and the $I_{PV}$ is monitored until it reaches back to $I_{mpp}$ again. The direction of perturbation can be determined by (8) and (9). If the $I_{PV}$ after load variation is smaller than $I_{mpp}$, this means that the load line shifted to the right side of the $I_{mpp}$, the increase in the duty cycle is required to bring the operating point back to $I_{mpp}$ as shown in Fig. 6. If the $I_{PV}$ is larger than $I_{mpp}$ after load variation, a reduction in the duty cycle with fixed perturbation is required to bring the operating point back to $I_{mpp}$. As a result, the response to the load variation will be much faster than the re-initialization of the metaheuristic approaches.

\[
(D_{mpp} = D_{mpp} - dD | I_{PV} - I_{mpp} > 0) \quad (8)
\]

\[
(D_{mpp} = D_{mpp} + dD | I_{PV} - I_{mpp} < 0) \quad (9)
\]

IV. IMPROVED TEAM GAME OPTIMIZATION ALGORITHM

Based on the observed behaviors of the PV system under different shading condition, solar intensity and load variations, the standard TGA has been improved as in the following section in order to achieve fast CS and rapid response to load variation.

A. Modification in the initialization of TGA

The position of a player $x$ is referred to $D$ which is the duty cycle of the converter. During initialization, the number of players should be selected based on the system, and it is recommended that they are placed at equal distance. The higher number of players would ensure the accuracy towards GMPP tracking but at a cost of high tracking time and vice versa. Therefore a trade-off between MPPT efficiency and CS is required. In this paper, the number of players is taken as four with a fixed initial position as 0.2, 0.4, 0.6 and 0.8 to cover the whole search space instead of random initial positioning. Since the duty cycle range is 0 to 1, the four players are adequate to track the GMPP for complex shading patterns. In the proposed modification, the players are not divided into two teams because all the players are required to converge towards the best player ($D_{best1}(t)$). By dividing the particles into two teams, there will be two players from each team to update their positions during the passing operation and may lead to a slow CS. In order to increase the CS, all four players are treated to be in a single team. Then, the two particles which have better performance corresponding to the powers $P_{best1}(t)$ and $P_{best2}(t)$, are used in the passing operators (10) and (11). As a result, the passing operation probability ($P = 0.5$) the passing operation will be carried out or else the mistake operation will be carried out.

B. Modification in passing operator

The passing operator (3) and (4) are modified to (10) and (11). This is because the $D$ range is between 0.1 to 0.9 and the multiplication of $x_{best}$ with two will update the player’s position outside the limit of $D$ in the initial cycles. Furthermore, instead of the multiplication of $r$ with $C_i(t+1)$, the factor $(1 - \frac{K}{K_{max}})$ is proposed in (11). $K$ is the number of iteration and $K_{max}$ is the maximum number of iteration. The random number $r$ is replaced with the dynamic variable which will become smaller with the increase in the number of iterations, making the convergence towards MPPT more accurate.

\[
C_i(t + 1) = D_{best1}(t) - D_i(t) \quad (10)
\]

\[
D_i(t + 1) = M + (1 - \frac{K}{K_{max}}) \cdot C_i(t + 1) \quad (11)
\]

In order to reduce the repetitive exploration of the same position, the two duty cycles ($D_{best1}(t)$ and $D_{best2}(t)$) which have better performance corresponding to the powers $P_{best1}(t)$ and $P_{best2}(t)$ are used in the passing operators (10) and (11).
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Fig. 7. Flowchart of the proposed method.

The \( M \) will be replaced with \( D_{\text{best1}}(t) \) to obtain \( D_1(t + 1) \), and with \( D_{\text{best2}}(t) \) to obtain \( D_2(t + 1) \). The other two duty cycles \( D_3(t) \) and \( D_4(t) \) are obtained by the generation of a random number which is between \( D_{\text{best1}}(t) \) and \( D_{\text{best2}}(t) \) as shown in (12). This can prevent the repetitive exploration of the same position another player had explored during the passing operation and thus it greatly improves the CS.

\[
\begin{align*}
D_3(t + 1) &= \text{rand}[D_{\text{best1}}(t), D_{\text{best2}}(t)] \\
D_4(t + 1) &= \text{rand}[D_{\text{best1}}(t), D_{\text{best2}}(t)]
\end{align*}
\]  

(12)

C. Modification in the mistake operator

A modification to the mistake operator is proposed by changing the random characteristic of \( z \) from \([-1, 1]\) to \( r \) which is between \([0, 1]\) as shown in (13). This is because the random negative multiplication can cause the \( D \) to go out of the limit and increases the CS. \( D_f(t) \) is a \( D \) selected from \( D_1(t) \) to \( D_4(t) \) randomly.

\[
D_f(t + 1) = D_f(t) + r \cdot (D_f(t) - D_i(t))
\]  

(13)

D. Modification in the termination condition

Two termination criteria are set in (14) to stop further exploration and stabilize the \( D \). \( P_{\text{best1}}(t) \) is the best power in the current iteration whereas \( P_{\text{best1}}(t - 1) \) is the best power in the previous iteration. \( \Delta D \) stands for the difference in the duty cycle value among the four particles. If (14) is satisfied, the termination condition will be met, and the \( D \) will get stabilized with \( D_{\text{best1}}(t) \) used as the duty cycle value of the converter. If the condition is satisfied means all the four particles are being close to each other. Once the termination condition met, the input voltage \( (V_{PV}) \), input current \( (I_{PV}) \), \( D_{\text{best1}}(t) \) and \( P_{\text{best1}}(t) \) will be regarded as \( V_{mpp}, P_{mpp}, D_{mpp}, \) and \( P_{mpp} \).

\[
\left(\frac{|P_{best1}(t) - P_{best1}(t - 1)|}{P_{best1}(t)}\right) \text{ AND } |\Delta D| < 0.05
\]  

(14)

E. To differentiate between MPP and load variation

Once the termination condition met, (15) is utilized to monitor the difference between the input power \( (P_{PV}) \) and \( P_{mpp} \). There are two reasons for \( P_{PV} \) changes while keeping the temperature constant which are irradiance/MPP changes and load variation.

\[
\frac{|P_{PV} - P_{mpp}|}{P_{mpp}} > 0.05
\]  

(15)

To differentiate between these two, the condition in (6) is utilized. If (6) is satisfied, there is a variation in solar intensity. The re-initialization of player’s positions will occur from subsection A as shown in Fig. 7 in order to determine the new peak point. If (6) is not satisfied, there is a load variation occurred and the program will jump to subsection F. In order to respond faster during load variation, the CC method is proposed to track back the MPP.

F. The constant current method for load variation

When the load variation condition occurs after the MPP is tracked, the \( I_{PV} \) varies from \( I_{mpp} \). If the \( I_{PV} \) is higher than \( I_{mpp} \) tracked as shown in (8), the subtraction of \( dD \) occurs until the power difference between the \( P_{PV} \) and \( P_{mpp} \) becomes near to 0. If the \( I_{PV} \) is smaller than \( I_{mpp} \), then the addition of \( dD \) occurs as shown in (9) till the \( P_{PV} \) becomes near to \( P_{mpp} \) and unsatisfied the condition of (15). The value of 0.05 has been chosen for \( dD \) based on trial and error, considering CS and MPPT efficiency. \( dD \) can be smaller but it will take more time to track back the MPP during load variations. It can be made higher for fast CS but there is a possibility of oscillation as condition (15) will satisfy again and again. Hence, a suitable value should be chosen to make the response of the system towards load changes faster and accurate. This approach for load variations can be integrated with any bio-inspired algorithm and can be implemented on any conventional isolated or non-isolated dc-dc converter without modifying the algorithm if there is any changes in the type of converter. Reducing the \( D \) will cause a reduction in PV current and vice versa for any conventional isolated or non-isolated dc-dc converter. Hence adjusting the \( D \) in comparison with \( I_{mpp} \) can easily track back the MPP by bringing the \( I_{PV} \) to \( I_{mpp} \).

V. RESULTS AND DISCUSSION

A. Experimental setup

Fig. 8 illustrates the block diagram of the experimental setup with components parameter using a boost converter. The switching frequency of 20 kHz is utilized. Fig. 9 shows the real-time experimental setup. The Chroma 62150H Solar Array Simulator (SAS) is utilized as a replacement of solar array to implement the different shading patterns of five multiple peaks accurately with five modules connected in series, as shown in Fig. 8. The Chroma GUI also helps to determine the MPPT efficiency, which is calculated by (16). Table 1 shows the PV array parameters of A10 Green Technology PV panel of 175 W. The Lecroy Waverunner 4Xi Digital Signal Oscilloscope (DSO) is used to capture the event of tracking and steady state,
illustrating \( P_{PV} \), \( V_{PV} \), \( I_{PV} \), and \( D \), as shown in Fig. 10. The DSpace (D1104) is utilized as a central brain to implement the proposed algorithm. The sampling time of 0.05s is chosen for the boost converter. The LEM voltage (LV-25P) and current sensor (LA-25NP) are used to scale down the voltage and current for DSpace since Analog to Digital Converter (ADC) requires \( V_{PV} \) and \( I_{PV} \) as input.

\[
\text{MPPT efficiency} = \frac{\text{Steady state power}}{\text{Maximum available power}} \times 100 \quad (16)
\]

Table I. AlOJ-S72-175 PV module at standard test conditions (STC).

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<thead>
<tr>
<th>Initials</th>
<th>( V_{oc} )</th>
<th>( I_{sc} )</th>
<th>( V_{mp} )</th>
<th>( I_{mp} )</th>
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<td>44 V</td>
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<td>36.6 V</td>
<td>4.78 A</td>
<td>175 W</td>
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**B. Different GMPP validation**

Four PSCs with complex five multiple peaks are tested to validate the proposed method. The red point on the P-V and I-V curves shows the stabilized tracked point which used to determine the MPPT efficiency. The shading patterns are established by setting the irradiance values for every five modules connected in series in Chroma GUI. The temperature is kept constant at 25°C.

First, the irradiance values are set at 1000 W/m², 900 W/m², 800 W/m², 700 W/m² and 600 W/m², and regarded as PSC-A for the GMPP at the extreme right. The GMPP was tracked in 1s with MPPT efficiency of 99.70%. The \( D_{mp} \) was at 0.33970, as shown in Fig. 10(a).

The PSC-B was set at 1000 W/m², 800 W/m², 700 W/m², 600 W/m² and 400 W/m², as shown in Fig. 10(b). The tracking time was 0.7s, with MPPT efficiency of 99.96% and \( D_{mp} \) of 0.38907.

Fig. 9. Experimental Setup.
The CC method was triggered and the MPP was tracked back when the load was varied from 30 Ω to 15 Ω, the re-initialization of players’ positions. As shown in Fig. 12 (b) when the load was varied from 30 Ω to 15 Ω, the re-initialization of player’s position occurs which makes the response towards load changes slow. The proposed hybridized CC method improved the response by 78.26% for the mentioned load variation condition and perform better during fast varying load conditions.

C. Dynamic GMPP variation validation

In the standard TGA, once the peak point is tracked after satisfying the termination condition, it cannot be changed due to the unavailability of the re-initialization of the player’s position. In the proposed algorithm, the ITGA will keep monitoring the $P_{PV}$ by using (15). As shown in Fig. 11, the shading pattern was changed to PSC-B after the GMPP for PSC-C was tracked and an increase in $V_{PV}$ and $I_{PV}$ were observed as compared to the tracked $V_{mpp}$ and $I_{mpp}$ under PSC-B. Thus, the re-initialization of players ($D_i(t)$) position is carried out to determine the new GMPP. The proposed method successfully tracks the GMPP for PSC-B.

D. Load variation validation

The load variation test was conducted with the help of two variable loads connected in parallel with a switch in between them, to validate the proposed hybridized CC method. As shown in Fig. 12(a), once the MPP for PSC-B was tracked, the load was varied from 30 Ω to 15 Ω. Then, the $I_{PV}$ increased and the $V_{PV}$ decreased as compared to the tracked $I_{mpp}$ and $V_{mpp}$ for 30 Ω load. This indicated the occurrence of load variation. The CC method was triggered and the MPP was tracked back in 0.25s. Afterward, the load was varied from 15 Ω to 30 Ω and it took 0.25s to track back the MPP. This modification for load variation resulted in a speedy response in comparison with the re-initialization of players’ positions. As shown in Fig. 12 (b) when the load was varied from 30 Ω to 15 Ω, the re-initialization of player’s position occurs which makes the response towards load changes slow. The proposed hybridized CC method improved the response by 78.26% for the mentioned load variation condition and perform better during fast varying load conditions.

E. Performance analysis of standard TGA with ITGA

To showcase the difference and advantage of ITGA based MPPT in comparison with the standard TGA for MPPT, the PSC-E with irradiance level of 1000 W/m², 800 W/m², 600 W/m², 400 W/m² and 200 W/m² was tested, as shown in Fig.
13. The standard TGA tracked the GMPP accurately with a slower speed in comparison with the ITGA based MPPT. Fig. 13 also provides evidence that most of the time $D$ is going out of the limit of the search space due to the multiplication of 2 in (3), $r$ in (4) and $z$ in (5) for standard TGA. The limit of $D$ in between 0.2 and 0.8 has been used to prevent the $D$ from leaving the search space. For the same shading pattern, the tracking time was reduced by 72.5% in the ITGA. Overall, ITGA can re-initialize for MPP changes, respond quickly to load variations with the CC method, reduce the repetition of the same $D$ during passing operation, lower power oscillation during tracking state and CS is faster than the standard TGA.

Fig. 13. Performance analysis of standard TGA with ITGA using PSC-E.

VI. COMPARISON WITH OTHER METAHEURISTIC APPROACHES

Since conventional MPPT algorithms are unable to track the GMPP for all PSCs, as stated in [22], they are not considered for comparison with the proposed method. The metaheuristic approaches for tracking the GMPP are extremely effective. Nevertheless, the method of exploration applied in search space by the different methods determines the superiority of one strategy over the other. In order to evaluate the effectiveness of our proposed method, the comparison is conducted against PSO, GWO, Jaya, and IDE under similar PSCs A-D. The PSO [26] is selected for comparison since it is regarded as a metaheuristic algorithm norm. The GWO is considered also as it only has one tuning parameter and it is stated in [27] that it performs better than PSO. Jaya [28] is also included for comparison as there is no tuning parameter required. Meanwhile, IDE [24] is considered mainly for the comparison of load variation. The tuning parameters for PSO, GWO and IDE are shown in Table III.

<table>
<thead>
<tr>
<th>Metaheuristic approach</th>
<th>Tuning Parameters values</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSO</td>
<td>$c_{1_{\text{max}}}=2$, $c_{1_{\text{min}}}=1$, $c_{2_{\text{max}}}=2$, $c_{2_{\text{min}}}=1$, $w_{\text{max}}=1$, $w_{\text{min}}=0.1$</td>
</tr>
<tr>
<td>GWO</td>
<td>$a=2$ to 0 update with each cycle.</td>
</tr>
<tr>
<td>IDE</td>
<td>$C=0.5$, $F_{\text{max}}=0.4$, $F_{\text{min}}=0.1$</td>
</tr>
</tbody>
</table>

The GMPP accuracy, tracking time and reducing oscillation around GMPP during the tracking state also depends on the termination condition. Various scholars have used various termination conditions. In this paper for PSO, GWO, Jaya, and IDE the same termination condition has been utilized as (17). If the power and $D$ difference are less than the threshold between each particle or if the maximum number of iterations is reached, the termination condition will be met. Maximum iterations are taken as 20. The threshold is taken as 5% for all approaches.

If ($\Delta P$ and $\Delta D < 5\%$) OR ($K > 20$) \hspace{1cm} (17)

The experimental results under the same test conditions for the aforementioned approaches in a comparative manner for each PSC (A-D) are shown in Fig. 14. Based on the tuning parameters mentioned in [26], the PSO tracked the GMPP precisely but with slow CS as compared to the others. With a single dynamic tuning parameter and a better CS, GWO has outperformed PSO.
Jaya can converge faster towards GMPP with the removal of the worst particle location for the next iteration position update. If replication of $D$ is avoided by another particle, Jaya can be quicker.

The $I_{PV}$ is high particularly for PSC-C and PSC-D due to the change of GMPP from the right to the left side of the P-V search space. PSO, GWO, Jaya, and IDE show higher power fluctuations for this condition. The high-power fluctuations can be reduced in our proposed method due to the avoidance of repetition of the same duty $D$ by another particles.

If any change occurs in $P_{PV}$ after the $P_{mppt}$ is tracked, PSO, JAYA and GWO will re-initialize the positions ($D_i(t)$) which causes slow response during load variations. The IDE proposed a unique condition for load variations that outperform the PSO, GWO, Jaya and our proposed method in terms of CS for load variations. A speedy approach towards load changes, tracking back the MPP in 100ms for all load variation conditions, as shown in Fig. 15, is proposed. However, the algorithm requires modification if a different type of converter is used. With the changing of converter topology, our proposed hybridized CC method for load variations does not require modification in the algorithm, and response speed is faster than re-initialization during load variations.

The swarm-based approaches (PSO, GWO, and Jaya) update the $D_i(t)$ position towards $P_{best}(t)$ after each iteration. There is a lot of repetitive exploration of the same duty cycle, as observed in Fig. 14(a)-(d), before satisfying the termination condition. It is one of the reasons that PSO, GWO, Jaya, and IDE take a longer time than ITGA to satisfy the termination condition. The IDE avoids the repetition of the same position by the same particle, but still, the issue of repetition by another particle exists. Whereas, our proposed method avoids the repetition of the same $D$ during the passing operator. However, there is a possibility that the proposed method repeats the $D$ during mistake operation, but the repetition of the same $D$ has been reduced heavily.

Based on Grade Point Average (GPA) inspired by [29], the effectiveness of the proposed method in comparison with the mentioned approaches can be determined. The algorithm complexity is made dependent on the number of tuning parameters and random number generators. The tuning parameters are often given a constant value based on trial and error. If there is no tuning parameter, it will be granted with a GPA of 4, one with 3, two with 2 and more than two with 1 GPA. If there are no random number generators in the updating equation of duty cycle, it will be granted with 4 GPA one with 3, two with 2 and more than 2 with 1 GPA. If the response to load variation is between 0 to 100ms, it will be granted with 4 GPA one with 3, two with 2 and more than 2 with 1 GPA. If the response to load variation is between 100ms to 1s, more than 1s with 2 GPA. If the algorithm requires modification with the change in the converter, the GPA of 2 will be granted, else 4. The MPPT efficiency and tracking time will not be constant with the change in the converter, the GPA of 2 will be granted, else 4. The MPPT efficiency and tracking time will not be constant for the same PSC due to the utilization of random numbers in these approaches. Therefore, each PSC is run twenty times for each approach to determine the average tracking time and average MPPT efficiency which has been demonstrated in Table IV. If the overall average tracking time is less than 1s, the GPA of 4 will be issued, between 1s to 2s with 3 and more than 2s with 2. Whereas, if the average MPPT efficiency is more than 99.5%, the GPA of 4 will be granted, between 99% to 99.5% with 3, between 98% to 99% with 2 and less than 98% with 1 GPA.

**TABLE IV. CGPA based comparison among PSO, GWO, Jaya, IDE and ITGA.**

<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td>Average Tracking Time</td>
<td></td>
<td>2.1s</td>
<td>1.4s</td>
<td>0.9s</td>
<td>1.6s</td>
<td>0.8s</td>
</tr>
<tr>
<td>MPPT Efficiency (%)</td>
<td></td>
<td>99.81</td>
<td>99.86</td>
<td>99.76</td>
<td>99.79</td>
<td>99.72</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td>99.68</td>
<td>99.77</td>
<td>99.61</td>
<td>99.74</td>
<td>99.78</td>
</tr>
<tr>
<td>Algorithm Complexity</td>
<td>Tuning parameters</td>
<td>3 (2 GPA)</td>
<td>1 (3 GPA)</td>
<td>0 (4 GPA)</td>
<td>2 (2 GPA)</td>
<td>1 (3 GPA)</td>
</tr>
<tr>
<td>Response to Load Variations</td>
<td>Random numbers</td>
<td>2 (2 GPA)</td>
<td>2 (2 GPA)</td>
<td>2 (2 GPA)</td>
<td>2 (2 GPA)</td>
<td>2 (2 GPA)</td>
</tr>
<tr>
<td>Modification in algorithm</td>
<td></td>
<td>4 GPA (No)</td>
<td>4 GPA (No)</td>
<td>4 GPA (Yes)</td>
<td>2 GPA (Yes)</td>
<td>4 GPA (No)</td>
</tr>
<tr>
<td>CGPA</td>
<td></td>
<td>2.67</td>
<td>3</td>
<td>3.17</td>
<td>2.83</td>
<td>3.33</td>
</tr>
</tbody>
</table>

Fig. 14. PSO, GWO, Jaya and IDE validation on (a) PSC-A (b) PSC-B (c) PSC-C and (d) PSC-D.

Fig. 15. Load variation test using IDE.
Based on the mentioned criteria, Table IV is filled up. The Cumulative GPA (CGPA) is calculated by using (18). According to the CGPA, the ITGA shows the highest CGPA of 3.33, which means it is constituted of a higher number of features and shows better performance in terms of output fluctuation, convergence time, and compatibility with all conventional dc-dc converters including faster response for load variations.

\[ \text{CGPA} = \frac{4 \times \text{GPA Achieved}}{\text{Total GPA}} \]  
(18)

VII. CONCLUSION

In this paper, a new metaheuristic approach, namely Improved Team Game Optimization Algorithm (ITGA) has been proposed. Different PSCs were tested and proven that the average tracking time is less than 1s. The average MPPT efficiency is 99.78%. In comparison with standard TGA, the tracking time is reduced by 72.5% while avoiding the repeat exploration of the same D during passing operation. The proposed load variation technique improves the response in tracking back the GMPP as compared to the re-initialization of the player's position by 78.26%. Based on CGPA, the effectiveness of the proposed method is determined by comparing it to PSO, GWO, Jaya, and IDE under similar test conditions. CGPA of 3.33 shows that the proposed method has a higher number of features with its applicability in any type of conventional isolated or non-isolated dc-dc converter without modifying the algorithm. The future work will focus on the enhancement of the metaheuristic algorithms with the capability to differentiate between the partially and uniformly shaded patterns effectively.

REFERENCES


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